INTERNATIONAL JOURNAL OF RESEARCH AND INNOVATION IN SOCIAL SCIENCE (IJRISS)
ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume X Issue IV April 2026

Markov Chain Modeling of Stochastic Nature of Rainfall in Nigeria

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DOI: https://doi.org/10.47772/IJRISS.2026.100400027

Received: 04 April 2026; Accepted: 13 April 2026; Published: 25 April 2026

ABSTRACT

This study investigates the stochastic behavior of rainfall in Nigeria using probabilistic modeling and Markov chain analysis. Recognizing the critical role of rainfall in agriculture, water resource management, and urban planning, the project captures inherent randomness, seasonal variability, and long-term trends in precipitation patterns. Monthly rainfall data from selected Nigerian cities were analyzed with WinQSB software to develop transition probability matrices for defined rainfall states: low, moderate, heavy, very heavy, and extremely heavy. The study derives transition probabilities, steady-state distributions, and recurrence times for different rainfall intensities. Analysis reveals significant persistence in low rainfall states and varied probabilities for transitions to higher intensities, offering insights into the likelihood of extreme rainfall events. Steady-state probabilities indicate the long-term frequency of each rainfall category, while recurrence times measure the average duration between similar events. Results confirm that Markov chain models are effective tools for predicting rainfall variability in a region characterized by climatic uncertainty. These findings have significant implications for enhancing early warning systems, optimizing agricultural practices, and guiding water resource management policies in Nigeria. Recommendations for future research include integrating hybrid models that combine traditional stochastic methods with machine learning techniques to further refine rainfall predictions and support adaptive climate strategies.

Keywords: Probability Modeling, Markov Chain Analysis, Precipitation Trends, Transition Probability, Steady State Distribution

INTRODUCTION

Stochastic models are particularly useful for rainfall analysis because they can account for irregularities, seasonality, and long-term climate trends. Unlike deterministic models, which rely on fixed equations, stochastic models incorporate probability distributions to describe the likelihood of different rainfall events (Box et al., 2015). These models can be classified into discrete-time and continuous-time processes, depending on whether rainfall data is observed at fixed intervals, such as daily or monthly, or continuously over time (Kumar & Shukla, 2019). Several stochastic approaches have been applied to rainfall prediction and climate studies, including Markov Chains, which model rainfall as a sequence of dependent events where the probability of future rainfall depends only on the current state (Kemeny & Snell, 2018), Poisson Processes, used to model the occurrence of rainfall events over time (Tijms, 2017), Autoregressive Integrated Moving Average (ARIMA) models, which combine time series techniques with stochastic components to predict rainfall trends (Box et al., 2015), and Hidden Markov Models (HMMs), which extend the Markov Chain concept by incorporating unobservable climatic variables that influence rainfall patterns (Al Mamum Panto et al, 2024). By using these techniques, researchers can simulate possible rainfall scenarios, estimate return periods for extreme rainfall events, and assess the impact of climate variability on precipitation patterns (Adeola et al., 2018). Rainfall is a fundamental component of the hydrological cycle, playing a crucial role in sustaining ecosystems, replenishing water bodies, and supporting agricultural production. In Nigeria, rainfall variability is influenced by both global climatic phenomena and regional weather systems. The country experiences a tropical climate with distinct wet and dry seasons, but the onset, duration, and intensity of rainfall vary significantly across different regions (Adeyemi et al., 2020). The southern region, closer to the Atlantic Ocean, receives high and evenly distributed rainfall, while the northern region experiences a shorter rainy season and prolonged dry periods, often leading to water scarcity and desertification (Adebayo et al., 2021). Understanding and predicting these rainfall patterns is essential for agriculture, water resource management, and disaster preparedness (NIMET, 2022). Due to the unpredictable nature of rainfall, traditional meteorological models struggle to accurately forecast precipitation patterns. This unpredictability is attributed to random fluctuations in atmospheric conditions, oceanic influences, and climate change effects (Olaniran & Summer, 2021). To address this challenge, researchers have turned to stochastic modelling, which allows for probabilistic predictions rather than deterministic outcomes. A stochastic process is a mathematical framework that describes randomly evolving systems, making it an ideal approach for modelling rainfall variations over time (Ross,2014). A stochastic process is defined as a collection of random variables indexed over time or space, describing how a system evolves in an uncertain environment (Ross, 2014). In the context of rainfall analysis, stochastic processes are used to capture the randomness and temporal dependence of precipitation patterns. Rainfall patterns often exhibit non-stationarity due to climate change and regional influences (Akinyele & Ogundipe, 2020). Discrete-time stochastic models are particularly relevant for precipitation studies because rainfall measurements are typically collected at discrete intervals (Tijms, 2017). Markov Processes, which are a special type of stochastic process, simplify rainfall modelling by assuming that the future state of the system depends only on the present state, not the entire past history (Kemeny & Snell, 2018). Markov Chains are one of the most widely used stochastic techniques for rainfall prediction. They assume that the probability of rainfall on a given day depends only on whether it rained on the previous day, making them suitable for analysing rainfall transition probabilities, such as wet-to-dry or dry-to-wet transitions (NIMET, 2022). A first-order Markov Chain expresses this mathematically, where the probability of future rainfall is conditioned only on the present state. Higher-order Markov Chains can incorporate additional past observations, improving prediction accuracy (Kumar & Shukla, 2019). In Nigeria, Markov Chain models have been successfully used to estimate rainfall probabilities in different climatic zones. Studies have applied a two-state Markov Chain to predict rainfall occurrences in northern Nigeria, demonstrating that rainfall persistence is higher during the peak wet season (Adeola et al., 2018). The Poisson Process is another stochastic model used to describe the random occurrence of rainfall events over time. This model assumes that rainfall events occur independently and at a constant average rate (Tijms, 2017). The probability of observing a certain number of rainfall events in a given time period can be calculated using the Poisson probability function. Poisson models are particularly useful for estimating the frequency of extreme rainfall events, such as heavy storms and flash floods (Ajayi & Omotosho, 2018). Time series analysis combines stochastic processes with statistical techniques to forecast future rainfall. The most commonly used time series models include Autoregressive (AR) Models, which predict future rainfall based on past values using regression techniques (Box et al., 2015), Moving Average (MA) Models, which smooth out short-term fluctuations in rainfall by averaging past observations, and ARIMA Models, which combine AR and MA models to account for trends, seasonality, and random noise (Kumar & Shukla, 2019). These models have been used to forecast rainfall patterns in Nigeria, demonstrating high predictive accuracy compared to traditional climate models (Oyebade, 2020). Rainfall variability is also affected by larger climate phenomena such as the El Niño-Southern Oscillation (ENSO), which influences rainfall patterns in West Africa (Nicholson, 2018). Stochastic models have been applied to quantify the relationship between ENSO phases and rainfall variability, allowing researchers to predict dry and wet spells with greater confidence. Incorporating climate indices into stochastic models enhances their predictive power, particularly in regions prone to extreme weather conditions (Adeyemi et al., 2020). Recent advancements in machine learning have further improved stochastic rainfall modelling. Hybrid models that combine stochastic techniques with neural networks and deep learning algorithms have shown promise in enhancing rainfall forecasting accuracy (Zhang et al., 2021). These models integrate historical rainfall data, atmospheric conditions, and stochastic processes to generate more precise rainfall predictions. While still in their early stages, such hybrid models hold potential for improving early warning systems and disaster preparedness in Nigeria and other climate-vulnerable regions. Rainfall is a highly variable and complex meteorological phenomenon that requires advanced modelling techniques for accurate prediction and analysis. Stochastic processes, particularly Markov Chains, Poisson Processes, and ARIMA models, provide robust frameworks for understanding rainfall patterns and forecasting future precipitation trends. By leveraging these models, policymakers and researchers can develop early warning systems, improve water resource management, and enhance agricultural planning. However, there remains a need for further research into hybrid stochastic models that integrate multiple techniques to improve rainfall forecasting accuracy in Nigeria.

Rainfall plays a vital role in shaping Nigeria's climate, agriculture, water resources, and overall ecosystem. However, the spatial and temporal distribution of rainfall in the country is highly unpredictable, leading to climatic extremes such as droughts and floods (Adeyemi et al., 2020). The variability in rainfall patterns is largely driven by factors such as climate change, atmospheric circulation, and regional topography (Olaniran & Summer, 2021). Given the irregular nature of rainfall, stochastic processes provide a powerful tool for analysing and predicting rainfall trends, helping researchers and policymakers make data-driven decisions.

A stochastic process is a mathematical model that describes a system's evolution in random or probabilistic terms over time (Box et al., 2015). In meteorology, stochastic models such as Markov Chains, Poisson Processes, and Autoregressive Integrated Moving Average (ARIMA) models have been extensively used to predict rainfall patterns (Kumar & Shukla, 2019). These models identify rainfall trends, estimate probability distributions, and simulate future precipitation scenarios, enabling better preparedness for weather-related disasters and agricultural planning. Nigeria's climate is influenced by the Inter-Tropical Discontinuity (ITD), which affects the onset, intensity, and cessation of rainfall across different regions (NIMET, 2022). The southern region receives higher and evenly distributed rainfall, while the northern region experiences shorter rainy seasons and prolonged dry periods (Adebayo et al., 2021). This variability has significant implications for crop production, water resource management, and urban planning. Several studies have attempted to model and predict rainfall patterns in Nigeria. For example, Oyebade (2020) applied time series analysis to investigate seasonal fluctuations in rainfall, while Ajayi and Omotosho (2018) used stochastic differential equations to analyse rainfall uncertainties. However, there remains a research gap in integrating multiple stochastic models to capture long-term rainfall trends and their impact on Nigeria's hydrological cycle. This study seeks to fill that gap by employing stochastic modelling techniques to analyse rainfall variability and forecast future precipitation patterns in Nigeria.

MATERIALS AND METHOD

The study adopts a quantitative research design, specifically a Markov Chain analysis approach, to investigate rainfall variability in Nigeria. Markov Chain analysis is appropriate because it enables the detection of random variations in rainfall patterns. The stochastic modelling technique is applied to describe and predict rainfall distribution by incorporating probabilistic methods. A major advantage of this approach is that it accounts for both deterministic and random elements of rainfall behaviour. By applying Markov Chains, the study aims to model the likelihood of rainfall occurrences based on historical data. This research also explores whether rainfall follows a stationary process or exhibits non-stationary behaviour due to climate change and anthropogenic factors.

The study area for this research encompasses four key locations in Nigeria: Benin, Ibadan, Ikeja, and Ijebu-Ode, each of which holds significant cultural, economic, and demographic importance. This study utilises secondary data obtained from the Central Bank of Nigeria (CBN), which provides historical data on various economic and environmental indicators. The dataset used for this research covers monthly rainfall measurements in Nigeria from January 2004 to November 2021. The CBN compiles and archives rainfall data as part of its macroeconomic and climate-related data collection efforts. The data was retrieved from the CBN's statistical database, ensuring that it meets standardised reporting methodologies for climate and environmental analysis. The dataset includes rainfall volume, frequency of rainy days, and spatial distribution across different regions of Nigeria, enabling a comprehensive stochastic analysis of rainfall patterns. The software used for the Data Analysis is WinQSB.

A Markov chain is a special type of stochastic process that follows the Markov property, which states that the future state of the process depends only on its present state, without influence from past states. Mathematically, for a discrete-time stochastic process represented as, where each belongs to a discrete state space, the process satisfies the Markov property if:

$$(Xn+1 = i|Xn, Xn-1, \dots, X_0 = P(Xn+1 = i|Xn) \; for \; all \; n \geq 0 \; and \; i \in S \; \dots\dots\dots(1)$$

A stochastic process exhibiting this property is called a Markov chain. A finite Markov chain can be characterised by transition probabilities:

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume X Issue IV April 2026

$$P_{ij} = (X_{n+1} = j | X_n = i) \; i, j \in S \text{.........(2)}$$

Where the sum of transition probabilities from any given state must equal one:

$$\sum_{j \in S} p_{ij} = 1 \; \forall \; i \in S$$

Representation,

$$P_{ij} = P\,(X_{t+1} = S_j | X_t = S_i) \text{..........(3)}$$

The transition probability matrix for the general states is given as:

$$\begin{matrix} P_{11} & P_{12} & P_{13} & P_{14} & P_{15} \\ \vdots & & \vdots & & \vdots \\ P_{51} & P_{52} & P_{53} & P_{54} & P_{55} \end{matrix}$$

1. **States:**

- **State S_i** = Low rainfall (denoted as L)
- **State S= moderate rainfall (denoted as M)**
- **State S_j** = Heavy rainfall (denoted as H)
- **State S = Very heavy rainfall (denoted as VH)**
- **State S = Extremely heavy rainfall (denoted as EH)**

2. Probabilities of moving between the two states (from month t to month t+1)

$$\begin{bmatrix} P(H \Rightarrow H) & P(H \Rightarrow L) \\ P(L \Rightarrow H) & P(L \Rightarrow L) \end{bmatrix} \text{.....................(4)}$$

This means:

P_{11} = P (L→ L) = Probability that the rainfall remains **low** in the next month, given that it is **low** this month.

P_{12} = P (l→ M) = Probability that the rainfall rise from Low to **Moderate** in the next month, given that it is **low** this month respectively for others

RESULT

Here we have the transition table of each rainfall with states low, moderate, heavy, very heavy, extremely heavy used for this study.

Table 3.1 Transition probability table for Benin

Transition	Low	Moderate	Heavy	Very heavy	Extremely heavy	Total
Low	26 Prob= 26/65=0.400	15 Prob= 15/65=0.2308	10 Prob= 10/65= 0.1538	5 Prob=5/65= 0.077	9 Prob=9/65=0.1385	65 1
moderate	11	7	8	4	1	31

	Prob= 11/31=0.35	Prob=7/31= 0.23	Prob= 8/31=0,26	Prob=4/31= 0.13	Prob=1/31=0.03	1
Heavy	12 Prob=12/30=0.4	4 Prob=4/30=0.2	6 Prob=6/30=0.2	5 Prob=5/30= 0.17	3 Prob=3/30 0.03	30 1
Very heavy	8 Prob=8/27=0.30	2 Prob=2/27=0.07	7 Prob=7/27=0.26	8 Prob=8/27= 0.30	2 Prob=2/27=0.07	27 1
Extremely heavy	5 Prob= 5/17=0.29	2 Prob=2/17=0.12	1 Prob=1/17=0.06	6 Prob =6/17=0.35	3 Prob=3/17=0.18	17 1

Now the transition probability matrix for Benin will be:

$$P = \begin{matrix} 0.4 & 0.2308 & 0.1538 & 0.077 & 0.1385 \\ 0.35 & 0.23 & 0.26 & 0.13 & 0.03 \\ 0.4 & 0.13 & 0.2 & 0.17 & 0.1 \\ 0.30 & 0.07 & 0.26 & 0.30 & 0.07 \\ 0.29 & 0.12 & 0.06 & 0.035 & 0.18 \end{matrix}$$

Interpretation of the Transition probability Matrix for the Rainfall

low to low (0.4): There is a 40% chance that the rainfall will remain low next month if it is low this month. This suggests a strong persistence of low rainfall.

Low to moderate (0.2308): There is a 23.08% chance that the rainfall will rise from low to moderate next month if it is low this month. This suggest that when the rain is low this month, it is likely to be moderate next month

Low to heavy (0.1538): There is a 15.38% chance that the rainfall will increase from low to heavy next month if it is low this month. This indicates a heavy likelihood of transitioning from low to heavy rainfall

Low to very heavy (0.077): There is a 0.77% chance that the rainfall rise from low to very heavy next month if it is low this month. This suggests that when rainfall is low this month, it is likely to increase next month.

Low to extremely heavy (0.1385): There is a 13.85% chance that the rainfall will rise from low to extremely heavy next month if it is low this month.

Moderate to low (0.35): There is a 35% chance that the rainfall will drop from moderate to low next month if it is moderate this month.

Moderate to moderate (0.23): There is a 23% chance that the rainfall will remain moderate next month, if it is moderate this month.

Stationary/steady steady-state probability distribution of Benin

The stationary distribution of a Markov chain describes the distribution of X_t after a sufficiently long time that

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume X Issue IV April 2026

the distribution of X_t does not change any longer. To put this notion in equation form, let π be a column vector of probabilities on the states that a Markov chain can visit that is; $\pi = \pi P$

Table 3.2 Key Results from WinQSB for Benin; the steady state and recurrence time.

	State name	Steady State probability	Recurrence time
1	Low	0.3626	2.7580
2	Moderate	0.1721	5.8106
3	Heavy	0.1877	6.3276
4	Very heavy	0.1719	5.8186
5	Extremely heavy	0.1058	9.4553

Therefore, π (0.3626, 0,1721, 0.1877, 0.1719, 0.1058) are the values of the steady states respectively.

Interpretation of the Steady-State Probabilities for Benin:

The steady-state probabilities represent the long-term behavior of this Markov process, meaning how frequently we expect to be in each state (low, moderate, heavy, very heavy, extremely heavy) after a long period, assuming the process has reached equilibrium (i.e., it is no longer changing from one state to the next).

Interpretation:

Low ($\pi1$=0.3626): 36.26% of the time, rainfall at Benin will be in the low long run.

This suggests that rainfall in Benin tend to stay in or return to low most of the time.

Moderate ($\pi2$=0.1721): 17.21% of the time, rainfall at Benin will be moderate in the long run. This indicates that while the moderate rainfall e is possible, it occurs much less frequently in the long term.

Heavy ($\pi3$=0.1877): 18.77% of the time, rainfall at Benin will be heavy in the long run. This indicates that while the heavy rainfall is possible, it occurs more frequently in the long term.

Very heavy ($\pi4$=0.1719): 17.19% of the time, rainfall at Benin will be very heavy in the long run. This indicates that while the very rainfall is possible, it occurs much frequently in the long term.

Extremely heavy ($\pi5$=0.1058): 10.58% of the time, rainfall at Benin will be extremely heavy in the long run. This indicates that while the extremely rainfall is possible, it occurs much more frequently in the long term.

Forecasting Future trend Behavior for Benin:

Given the steady-state probabilities and recurrence times, we can use this information to forecast future behavior of the system:

$$P = \begin{array}{cccccc} 0.2 & 0.348 & 0.3601 & 0.3623 & 0.3625 \ldots\ldots & .0.3626 \\ 0.2 & 0.156 & 0.1670 & 0.1710 & 0.1719 \ldots\ldots & 0.1721 \\ 0.2 & 0.186 & 0.1898 & 0.1880 & 0.1877 \ldots & .0.1877 \\ 0.2 & 0.206 & 0.1780 & 0.1730 & 0.1721 \ldots\ldots. & 0.1719 \\ 0.2 & 0.104 & 0.1051 & 0.1058 & 0.1058 \ldots\ldots & ..0.1058 \end{array}$$

The matrix indicates the future trend where the first column is the initial probabilities and the last column is the steady state probability.

For Ikeja

The steady states are (0.3576, 0.3016, 0.1513, 0.1422, 0.0472). The Recurrence times are (2.796, 3.3153, 6.6091, 7.0308, 21.1815)

For Ibadan

The steady states are (0.2924, 0.2642, 0.2270, 0.1183, 0.0481)

The Recurrence times are (3.4203, 3.7847, 3.6100, 8.4537, 20.7844)

For Ijebu Ode

The steady states probabilities are (0.4195, 0.2631, 0.1411, 0.1218, 0.054)

The Recurrence times are (2.3838, 3.8004, 7.0860, 8.2102, 18.3649)

Forecasting Future trend Behavior

Over the next few months, it is expected that the system will be in high state with a very high probability, but if the system ever transitions to Low, it will be much less frequent and take a long time to return. Results obtained for other locations also showed similar forecast for all the Location considered.

SUMMARY OF FINDINGS

The Markov chain analysis of rainfall in Benin City reveals interesting patterns and probabilities for different rainfall states over time. If rainfall is low this month, there is a 40% chance that it will remain low next month, indicating a strong persistence of low rainfall. In the long run, Benin City is likely to experience low rainfall 36.26% of the time, with an average recurrence time of 2.76 months. There is a 23.08% chance that low rainfall will transition to moderate next month, and moderate rainfall is expected to occur 17.21% of the time in the long run, with an average recurrence time of about 5.81 months. The chance of low rainfall increasing to heavy next month is 15.38%, with heavy rainfall occurring 18.77% of the time in the long run and recurring every 6.33 months on average. The probability of low rainfall transitioning to very heavy next month is 0.77%, and very heavy rainfall is expected to occur 17.19% of the time in the long run, with a recurrence time of about 5.82 months. For extremely heavy rainfall, there is a 13.85% chance that low rainfall will increase to this state next month, with extremely heavy rainfall occurring 10.58% of the time in the long run and recurring every 9.46 months on average.

Based on the Markov chain analysis of rainfall in Ikeja, Lagos, we can observe distinct patterns and probabilities for different rainfall states over time. If rainfall is low this month, there is a 43.75% chance it will remain low next month, indicating a strong persistence of low rainfall. In the long run, Ikeja is likely to experience low rainfall 35.76% of the time, with an average recurrence time of approximately 2.80 months. There is a 34% chance that low rainfall will transition to moderate next month. Moderate rainfall is expected to occur 30.16% of the time in the long run, with an average recurrence time of about 3.32 months. The chance of low rainfall increasing to heavy next month is 5%, and heavy rainfall is expected to occur 15.13% of the time in the long run, recurring every 6.61 months on average. For very heavy rainfall, the probability of low rainfall transitioning to very heavy next month is 8%, and very heavy rainfall is expected to occur 14.22% of the time in the long run, with a recurrence time of approximately 7.03 months. Lastly, there is a 2% chance that low rainfall will increase to extremely heavy next month, with extremely heavy rainfall occurring 4.72% of the time in the long run and recurring every 21.18 months on average.

Result on the Markov chain analysis of rainfall for Ibadan showed distinct patterns and probabilities for different rainfall states over time. If rainfall is low this month, there is a 51% chance it will remain low next

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume X Issue IV April 2026

month, indicating a strong persistence of low rainfall. In the long run, Ibadan is likely to experience low rainfall 29.24% of the time, with an average recurrence time of approximately 3.42 months. There is a 34% chance that low rainfall will transition to moderate next month. Moderate rainfall is expected to occur 26.42% of the time in the long run, with an average recurrence time of about 3.78 months. The chance of low rainfall increasing to heavy next month is 5%, and heavy rainfall is expected to occur 22.70% of the time in the long run, recurring every 3.61 months on average. For very heavy rainfall, the probability of low rainfall transitioning to very heavy next month is 8%, and very heavy rainfall is expected to occur 11.83% of the time in the long run, with a recurrence time of approximately 8.45 months. Lastly, there is a 2% chance that low rainfall will increase to extremely heavy next month, with extremely heavy rainfall occurring 4.81% of the time in the long run and recurring every 20.78 months on average.

Markov chain analysis of rainfall in Ijebu Ode also reflect distinct patterns and probabilities for different rainfall states over time. If rainfall is low this month, there is a 51% chance it will remain low next month, indicating a strong persistence of low rainfall. In the long run, Ijebu Ode is likely to experience low rainfall 41.95% of the time, with an average recurrence time of approximately 2.38 months. There is a 30% chance that low rainfall will transition to moderate next month. Moderate rainfall is expected to occur 26.31% of the time in the long run, with an average recurrence time of about 3.80 months. The chance of low rainfall increasing to heavy next month is 7%, and heavy rainfall is expected to occur 14.11% of the time in the long run, recurring every 7.09 months on average. For very heavy rainfall, the probability of low rainfall transitioning to very heavy next month is 10%, and very heavy rainfall is expected to occur 12.18% of the time in the long run, with a recurrence time of approximately 8.21 months. Lastly, there is a 2% chance that low rainfall will increase to extremely heavy next month, with extremely heavy rainfall occurring 5.4% of the time in the long run and recurring every 18.36 months on average.

CONCLUSION

The Markov chain analysis of rainfall in Benin City, Ijebu Ode, Ikeja, and Ibadan reveals distinct patterns and probabilities for different rainfall states over time. If rainfall is low this month, there is a 51% chance it will remain low next month, indicating a strong persistence of low rainfall. In Benin City, low rainfall has a 40% chance of remaining low, occurring 36.26% of the time in the long run. Moderate rainfall occurs 17.21% of the time, heavy rainfall 18.77%, very heavy rainfall 17.19%, and extremely heavy rainfall 10.58%. Recurrence times indicate that low rainfall returns every 2.76 months, moderate every 5.81 months, heavy every 6.33 months, very heavy every 5.82 months, and extremely heavy every 9.46 months.

In Ijebu Ode, low rainfall also has a strong persistence with a 51% chance of remaining low, occurring 41.95% of the time in the long run. Moderate rainfall occurs 26.31% of the time, heavy rainfall 14.11%, very heavy rainfall 12.18%, and extremely heavy rainfall 5.40%. Recurrence times for Ijebu Ode show that low rainfall returns every 2.38 months, moderate every 3.80 months, heavy every 7.09 months, very heavy every 8.21 months, and extremely heavy every 18.36 months.

For Ikeja, low rainfall has a 43.75% chance of remaining low, occurring 35.76% of the time in the long run. Moderate rainfall occurs 30.16% of the time, heavy rainfall 15.13%, very heavy rainfall 14.22%, and extremely heavy rainfall 4.72%. Recurrence times indicate that low rainfall returns every 2.80 months, moderate every 3.32 months, heavy every 6.61 months, very heavy every 7.03 months, and extremely heavy every 21.18 months.

In Ibadan, low rainfall has a 51% chance of remaining low, occurring 29.24% of the time in the long run. Moderate rainfall occurs 26.42% of the time, heavy rainfall 22.70%, very heavy rainfall 11.83%, and extremely heavy rainfall 4.81%. Recurrence times show that low rainfall returns every 3.42 months, moderate every 3.78 months, heavy every 3.61 months, very heavy every 8.45 months, and extremely heavy every 20.78 months.

Markov chain analysis has effectively identified trends, variations, and patterns in historical rainfall data across these cities. The analysis reveals that low rainfall tends to persist in all cities, with varying probabilities for transitioning to other states. The steady-state probabilities and recurrence times provide valuable insights into the long-term behavior of rainfall in each city. This information can be used for planning and decision-making in various sectors, such as agriculture, water resource management, and urban planning, to better prepare for and adapt to the variability of rainfall patterns in Nigeria.

Additionally, the analysis successfully developed Markov chains for each city, capturing the variability of rainfall patterns over time. These Markov chains provide probabilities of transitioning between different rainfall states from one month to the next, offering a comprehensive understanding of how rainfall patterns change over time. This detailed analysis provides valuable insights into the long-term behavior of rainfall, helping to understand trends and predict future patterns.

In conclusion, the Markov chain analysis has met both objectives by identifying trends, variations, and patterns in historical rainfall data and developing a Markov chain that captures the variability of rainfall patterns over time.

RECOMMENDATIONS

Agricultural Planning and Management: The Markov chain analysis of rainfall patterns in Benin City, Ijebu Ode, Ikeja, and Ibadan reveals that low rainfall tends to persist in all cities, with varying probabilities for transitioning to other states. To mitigate the impact of low rainfall on agriculture, it is recommended to invest in drought-resistant crops and efficient irrigation systems. Farmers should be encouraged to adopt water-saving techniques and diversify their crop choices to enhance resilience against fluctuating rainfall patterns.

Water Resource Management: The analysis highlights the variability and recurrence times of different rainfall states. Effective water resource management strategies should be developed to ensure adequate water supply during periods of low rainfall. It is advisable to construct additional water storage facilities, such as reservoirs and dams, to capture and store rainwater during heavy rainfall periods. Implementing water conservation measures and promoting the use of alternative water sources, such as groundwater, can also help in managing water resources efficiently.

Urban Planning and Infrastructure Development: Urban planners and policymakers should consider the insights from the Markov chain analysis when designing and developing infrastructure in these cities. To address the challenges posed by variable rainfall patterns, it is important to invest in robust drainage systems and flood management infrastructure. Incorporating green infrastructure, such as rain gardens and permeable pavements, can help in mitigating the impact of heavy rainfall and reducing urban flooding risks.

Climate Change Adaptation: Given the long-term probabilities and recurrence times of different rainfall states, it is crucial to integrate climate change adaptation measures into planning and policy frameworks. Developing early warning systems and providing timely weather forecasts can help communities prepare for and respond to extreme weather events. Additionally, raising awareness about the potential impacts of climate change on rainfall patterns can encourage proactive measures to enhance resilience.

Research and Data Collection: Continuous monitoring and data collection on rainfall patterns are essential for improving the accuracy of future analyses. Establishing a comprehensive network of weather stations and investing in advanced meteorological technologies can enhance the quality of data collected. Collaborating with research institutions and experts in climatology can provide valuable insights and support evidence-based decision-making. These recommendations aim to enhance the resilience of agriculture, water resources, urban infrastructure, and communities against the variability of rainfall patterns in Nigeria. By implementing these strategies, it is possible to better prepare for and adapt to the challenges posed by changing rainfall patterns and contribute to sustainable development.

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